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Estimating Rice Grain Yield Potential Using Normalized Difference Vegetation Index

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ABSTRACT

Normalized difference vegetation index (NDVI) measurements have the potential to improve mid-season N crop management decisions in rice (*Oryza sativa* L.). The objectives of this study were to determine the optimum sensing timing and establish a yield prediction model using NDVI measurements acquired with the GreenSeeker sensor. Weekly sensor readings were collected over a 5-wk period from multi-rate N fertilization trials established at six different locations from 2008 to 2010. Categorizing sensing timing by growth stage demonstrated that late sensing timings beyond panicle differentiation (PD) were impractical and reduced yield potential estimation as opposed to panicle initiation (PI) and PD timings. Regression analysis produced two viable yield potential prediction equations at PI (r^2 = 0.36) and PD (r^2 = 0.42). When sensor timings were categorized by cumulative growing degree days (GDD), 1301 to 1500 and >2100 GDD groupings (r^2 = 0.28 and 0.37, respectively) were found to be inferior yield predictors as compared with 1501 to 1700 and 1701 to 1900 GDD groupings (r^2 = 0.41 for both). In almost all instances, normalization of NDVI data using days from seeding (DFS; NDVI/DFS) or GDD (NDVI/GDD) did not improve yield potential prediction as compared with NDVI alone. Yield potential, response index, and N response to fertilization are the three major components needed to produce a working algorithm capable of predicting mid-season N fertilization needs in rice. The four yield prediction models gleaned from this study provide the yield potential component for this algorithm. Multiple yield prediction models give crop managers freedom to select a model based on either physical growth stage or by accumulated GDD units.

Nitrogen fertilizer is applied at greater rates than any other plant nutrient making it the most expensive fertilizer input in rice production (Fageria et al., 1997). A need-based application of N fertilizer plays an important role in developing more profitable and environmentally-sound rice production system. Developing a reliable soil test for N availability is a major challenge in any crop production system because of the dynamic behavior of N in the soil. In the absence of reliable soil test for N, crop yield level has become one of the main criteria in making N recommendations. For example, an N recommendation can be based on a yield goal, which can be determined by the recent 5-yr crop yield average +30% (Dahnke et al., 1988; Johnson, 1991). The yield goal concept employs the premise that N, both indigenous and supplemental, should be maintained at levels that optimize crop production and balance N inputs with losses (Stanford, 1973). However, application of the yield goal concept to derive N recommendations may not be the best option when there is uncertainty on establishing a realistic yield goal. In addition, the yield goal concept lacks precision because it does not account for both spatial and temporal variability in yield.

Appropriate N application rates in rice production in the mid-southern United States are established by each state based on multi-year and multi-site N response trials then further refined for specific variety, cultural management, and soil type (Guindo et al., 1994; Snyder and Slaton, 2002; Dunn and Stevens, 2006; Norman et al., 1997, 2000; Harrell et al., 2011). These established N rates are either applied one time at preflood or in split applications. A single, preflood N rate application scheme was reported to be more efficient than a two- or three-way split application (Norman et al., 2003; Bond and Bollich, 2007). However, the two- or three-way split application remains the predominant N application scheme by mid-southern U.S. rice producers in drill-seeded, delayed flood rice production systems. The split N application is preferred by rice producers for several reasons: first, even distribution of fertilizer from a single application is difficult and second, establishment of a permanent flood in a timely manner and maintaining the permanent flood throughout the season can be problematic (Snyder and Slaton, 2002). In these split N application scenarios where there is a need for a mid-season N application, there are several methods that can be used to determine the mid-season N rate. Wells et al. (1989), found that a mid-season N rate could be determined using a rice plant gauge which estimated plant biomass and total N uptake. According

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Abbreviations: DFS, days from seeding; GDD, growing degree days; NDVI, normalized difference vegetation index; PD, panicle differentiation; PI, panicle initiation; YP, yield potential.

Table 1. Agronomic information on variety by N trials conducted at different sites in Louisiana and Mississippi, 2008–2010.

Year	Site	Variety	Planting	Panicle initiation	Panicle differentiation	50% Heading	Harvest date	Yield†
			date‡					kg ha^{-1}
2008	Crowley, LA	Catahoula	25 Mar.	26 May (61) ‡	9 June (74)	8 July (90)	11 Aug.	9434
2008	Crowley, LA	CL131	25 Mar.	26 May (61)	9 June (74)	8 July (90)	13 Aug.	8864
2008	Crowley, LA	Neptune	25 Mar.	26 May (61)	9 June (74)	8 July (90)	15 Aug.	8835
2008	Rayville, LA	Neptune	25 Apr.	10 June (45)	17 June (52)	14 July (72)	10 Sept.	10308
2008	Stoneville, MS	Catahoula	21 Apr.	18 June (57)	24 June (63)	24 July (87)	15 Sept.	7225
2009	Rayville, LA	Catahoula	23 Apr.	22 June (59)	29 June (66)	20 July (80)	26 Aug.	9164
2009	Rayville, LA	CL151	23 Apr.	22 June (59)	29 June (66)	20 July (80)	26 Aug.	10785
2009	Rayville, LA	Neptune	23 Apr.	22 June (59)	29 June (66)	20 July (80)	26 Aug.	12138
2009	Stoneville, MS	Catahoula	22 Apr.	19 June (57)	30 June (68)	30 July (87)	28 Aug.	7422
2010	Crowley, LA	Catahoula	14 Mar.	25 May (70)	1 June (76)	25 June (94)	6 Aug.	9744
2010	Crowley, LA	CL151	14 Mar.	25 May (70)	1 June (76)	25 June (94)	6 Aug.	10076
2010	Crowley, LA	Neptune	14 Mar.	25 May (70)	1 June (76)	25 June (94)	6 Aug.	11106
2010	Lake Arthur, LA	CL151	15 Mar.	25 May (71)	1 June (77)	22 June (92)	2 Aug.	10013
2010	Stoneville, MS	Catahoula	28 Apr.	9 June (41)	16 June (48)	18 July (73)	23 Aug.	8153
2010	Leland, MS	Catahoula	13 Apr.	8 June (55)	15 June (62)	10 July (80)	18 Aug.	8747
2010	Boyle, MS	Catahoula	16 Apr.	15 June (59)	20 June (64)	20 July (89)	25 Aug.	9066

† Mean yield.

‡Values in parentheses are days required to reach specific growth stages from planting.

to Ntamatungiro et al. (1999), rice gauge-dry matter estimates produced a more reliable estimate of total N accumulation than Y-leaf N concentrations and Soil Plant Analysis Development (SPAD) readings. A modified mid-season N decision tool using visual and digital measurements of rice yield response to N was proposed by Stevens et al. (2008). Mapping of rice grain yield within a field is possible through the use of a yield monitor. This precision farming tool can provide crop yield information which is often used to fine-tune future crop N applications. However, yield monitors can document seasonal variability across field and the accumulated yield maps from past seasons may not be useful for subsequent years since the patterns of spatial variability within a field are not consistent every year (Asim, 2000).

Using rice dry matter for gauging a mid-season N rate recommendation is similar to the concept employed using the sensor-based N decision tool developed for wheat (*Triticum aestivum* L.) and corn (*Zea mays* L.) except that this tool estimates biomass using canopy reflectance-based vegetation indices as an index of crop yield potential (Raun et al., 1999; Teal et al., 2006; Tubaña et al., 2008). The calibrated relationship of vegetation index and grain yield is a component of the sensor-based N decision tool that is used for predicting yield potential described as the grain yield achievable with no additional N fertilization (Raun et al., 2002). Implementing the sensor-based N decision tool in wheat and corn production systems resulted in improved N use efficiency and economic returns, and a reduction in residual soil N content and apparent N loss (Raun et al., 2002; Li et al., 2008; Tubaña et al., 2008).

The reported benefits of deriving an N recommendation from sensor-based estimates of yield potential in wheat and corn justifies the need to conduct similar research in rice. Several studies have documented the potential use of remote sensing technology to monitor and evaluate rice N status (Xue et al., 2004; Lee et al., 2008). Others have used canopy reflectance readings to quantify rice yield, biomass, and leaf area index (Casanova et al., 1998; Xiao et al., 2002; Chang et al., 2005). A timely acquisition of rice yield potential where the influence of spatial and temporal variability can be accounted is possible using remote sensing. A field-based prediction of rice yield potential using remote sensing technology can be used in generating in-season, field-to-field maps of yield distribution in addition to providing N fertilizer application prescriptions. Regardless of the application goal, either for generating yield maps or deriving a mid-season N fertilization rate, an established relationship between canopy reflectance vegetation indices and measured grain yield is needed for mid-southern U.S. rice production systems. The objectives of this study were to determine optimum sensing timing where NDVI and grain yield have a strong relationship near established commercial mid-season N fertilizer application timing and to establish a yield potential predictive model for mid-southern U.S. commercial rice production systems using NDVI.

MATERIALS AND METHODS

This study was conducted from 2008 to 2010 at different locations in Louisiana and Mississippi, including the Louisiana State University Agricultural Center Rice Research Station near Crowley, LA (30°14′48″ N, 92°21′7″ W); Mississippi State University Delta Research and Extension Center in Stoneville, MS (33°25′56″ N, 90°54′08″ W); and commercial rice production fields in Lake Arthur, LA (30°02′47″ N, 92°38′46″W); Rayville, LA (32°33′08″ N, 91°43′19″ W); Leland, MS (33°30′22″ N, 90°49′56″ W); and Boyle, MS (33°40′41″ N, 90°44′10″ W). Biomass, sensor readings, and grain yield were collected from multiple N response trials established at each location. Table 1 provides detailed information on cultivars used, average grain yield, dates of different growth stages and field operations. Soil samples were collected from each site for characterization and fertilizer recommendations. Chemical properties and classification of the soil from the sites are summarized in Table 2. Nitrogen rates were 0, 33, 67, 100, 134, 168, 202, and 235 kg ha^{-1}. An additional N rate of 269 kg ha^{-1} was included for sites in Mississippi in all years while and additional N rate of 302 kg ha^{-1} was included in 2010 for sites in Louisiana. For each trial, preflood N treatments were replicated four times and arranged in a randomized complete block design.

Table 2. Type, classification and chemical properties of soils from the different sites in Louisiana and Mississippi where the variety by N trials were established, 2008–2010.

Year	Location	Soil series	Classification	OM‡	pH	P	K	S	Zn
				Chemical properties†					
				%		mg kg^{-1}			
2008	Crowley, LA	Crowley silt loam	fine, smectitic, thermic Typic Albaqualfs	1.3	6.8	11	73	12	6.2
2008	Rayville, LA	Perry clay	very fine, smectitic, thermic Chromic Epiaquerts	2.4	7.3	35	254	33	8.0
2008	Stoneville, MS	Sharkey clay	very-fine, smectitic, thermic Chromic Epiaquerts	2.3	8.1	95	275	85	2.0
2009	Crowley, LA	Crowley silt loam	fine, smectitic, thermic Typic Albaqualfs	1.3	7.0	22	61	15	6.9
2009	Rayville, LA	Perry clay	very fine, smectitic, thermic Chromic Epiaquerts	2.5	7.4	23	238	26	3.7
2009	Stoneville, MS	Sharkey clay	very-fine, smectitic, thermic Chromic Epiaquerts	2.6	8.0	96	345	185	2.7
2010	Crowley, LA	Crowley silt loam	fine, smectitic, thermic Typic Albaqualfs	1.2	7.1	4	52	7	3.4
2010	Lake Arthur, LA	Kaplan silt loam	fine, smectitic, thermic Aeric Chromic Vertic Epiaqualfs	1.1	4.5	19	115	22	1.7
2010	Stoneville, MS	Sharkey clay	very-fine, smectitic, thermic Chromic Epiaquerts	2.2	8.2	100	260	85	2.0
2010	Leland, MS	Forestdale silt loam	fine, smectitic, thermic Typic Endoaqualfs	1.2	6.8	23	82	85	0.5
2010	Boyle, MS	Sharkey clay	very-fine, smectitic, thermic Chromic Epiaquerts	0.8	7.1	55	130	52	0.9

† For LA: Soil pH was measured from a 1:1, water/soil ratio. Mehlich-3 extraction followed by ICP analysis was used for P, K, S, and Zn determination. For MS: Soil pH was measured from a 2:1 water/soil ratio. Lancaster extractant was used for soil available nutrient concentration. Sulfur was estimated based on organic matter content.
‡ OM–Walkley–Black method.

The rice was produced under a drill-seeded, delayed-flood cultural system. If recommended by soil testing, P, K, and Zn fertilizers were applied as triple superphosphate (46% P_2O_5), muriate of potash (60% K_2O) and zinc sulfate (36% Zn), respectively. Planting occurred in mid-March for Crowley and Lake Arthur sites while Rayville and all sites in Mississippi were accomplished in mid- to late April (Table 1). Rice was seeded to a depth of 4 cm at 300 seeds m^{-2} using a small-plot grain drill equipped with double-disc openers and press wheels. The length of each plot was 4.9 m consisting of seven rows with 20-cm spacing. Rice seedlings were allowed to grow until 4- to 5-leaf stage of development under aerobic conditions before flooding the field to a depth of approximately 15 to 20 cm. Fertilizer N treatments were broadcast 1 d before permanent flood establishment using urea (46% N). At harvest, a plot combine equipped with a computerized weigh and moisture system was used to collect and compute grain yield.

The NDVI readings were collected on a weekly basis for five consecutive weeks starting at PI using a GreenSeeker handheld sensor (NTech Industry Inc., Ukiah, CA). The sensor measured the canopy reflectance readings at specific wavelengths in red (RED, 670 ± 10 nm) and the near infrared (NIR 780 ± 10 nm) regions of the spectrum. Reflectance values at these regions were used to compute NDVI as $(R_{NIR} - R_{RED})/(R_{NIR} + R_{RED})$. The measurement of canopy reflectance was performed by placing the sensor head directly above the rice canopy in the nadir position with a distance consistently held at approximately 1 m. Speed of sensing was kept at a relatively constant pace obtaining an average of 45 readings with a 61 cm scanned line width. Physiological stages of development were evaluated by splitting the main stem from a random rice plant from the first replication of each variety fertilized with 134 kg N ha^{-1}. The PI stage of development was determined when internode elongation began, by visually observing a green band at the lowermost internode which briefly occurs just before its elongation. Panicle differentiation was determined when the internode elongated to approximately 1.5 cm and the differentiated panicle was first visible. The PI and PD developmental stages can be separated by as little as 3 to 5 d (Moldenhauer and Gibbons, 2003); however, the actual time between the two stages of development is dependent on variety and thermal energy accumulation during that time period (Walker, 2008).

Total aboveground biomass samples were collected at PD and 50% heading. The 50% heading stage of development was determined when 50% of the rice panicles had emerged from the boot. Chang et al. (2005) reported that growth stages between panicle formation and heading would be the best period for calibrating spectral vegetation indices with rice yield. In addition, these stages are important for interpreting rice N status (Cui and Lee, 2002; Ntanos and Koutroubas, 2002).

Statistical analysis was performed using SAS software (SAS Institute, 2003). Regression analyses were conducted using both PROC NLIN and PROC REG. Relationships were determined for biomass collected at PD and 50% heading with grain yield, and for NDVI readings collected at different times with grain yield. The cumulative growing degree days [(Tmax + Tmin)/2 – 10°C] and the number of days from seeding were determined for each sensing. These two variables were used to group and standardize NDVI readings before regression analysis similar to procedures performed by Raun et al. (2002) and Teal et al. (2006).

RESULTS AND DISCUSSION

Total aboveground biomass has been previously shown to be closely associated with rice grain yield and is important to access mid-season N needs in commercial rice production (Wells et al., 1989). Increasing total crop biomass is necessary to achieve higher grain yields (Evans and Fischer, 1999). A positive association between total aboveground biomass collected at PD and 50% heading and rice grain yield was observed in this study (Fig. 1). This observation agrees with previously published relationships which validated that increasing biomass increases rice grain yield (Akita, 1989). However, it must be pointed out that using biomass alone as a basis to derive the rice mid-season N requirement poses a limitation since biomass production does not always translate to proportionate increases in grain yield. When biomass production nears its maximum, rice becomes more susceptible to lodging (Setter et al., 1997) and disease incidence (Slaton et al., 2003, 2004), which can result in a reduction in grain yield. Similar to previous studies (Vergara, 1988; Setter et al., 1997), we also observed that grain yield did not always steadily increase with increasing biomass, particularly when biomass production approached its potential maximum. Significant

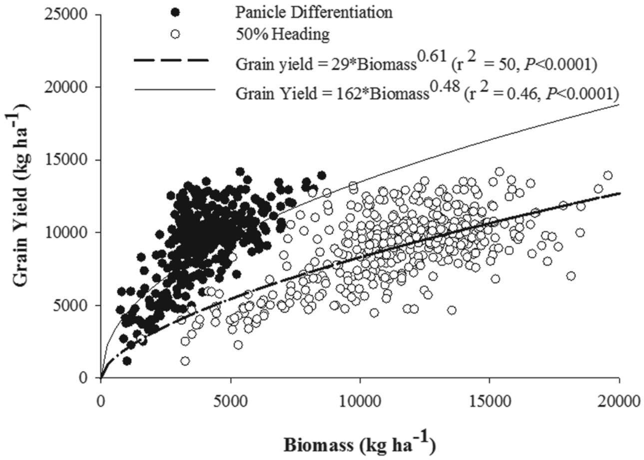

Fig. 1. Relationship of measured biomass at panicle differentiation (PD) and 50% heading with grain yield.

($P < 0.001$) relationships between grain yield and total aboveground biomass collected at PD and 50% heading were observed and were best regressed using a power function. Approximately 50 and 46% of the variation in rice grain yield was explained by total aboveground biomass at PD and 50% heading, respectively.

An in-field, nondestructive estimation of total aboveground biomass could be used as a surrogate to untimely, destructive methodologies currently employed to obtain rice biomass samples. Using canopy reflectance-estimates of biomass has the potential to increase the precision of predicting rice grain yield potential since it would account for some of the temporal and spatial variability. The NDVI-estimated biomass readings were grouped first according to growth stage and second according to GDD groupings and were then regressed with grain yield to evaluate this prospective. Resulting coefficients of determination (r^2) from these analyses are presented in Table 3. A power function best fit the data from both the growth stage and GDD groupings. The ability of NDVI to predict rice grain yield was similar between the PI and PD stages of development as illustrated by the similar r^2 values and regression equations (Table 3 and Fig. 2). The similarities between the two sensing times could be partially explained by the typically short developmental period between PI and PD in rice. The similarities are somewhat desirable since mid-season fertilization in mid-southern U.S. rice production typically occurs during the 1 wk average time period between PI and PD for most currently grown mid-southern U.S. rice cultivars (Norman et al., 2003). A much lower fit ($r^2 = 0.26$) resulted between NDVI and grain yield at the 50% heading stage of development. Using late season NDVI measurements in corn to estimate grain yield was also found to be problematic and was associated with the inability of the sensor to distinguish variation due to canopy closure (Teal et al., 2006). The reduced predictive ability at 50% heading in the current study is most likely associated with the uneven emergence of panicles into the sensor field of view.

Prediction of the rate and length of different stages of morphological developmental in plants has been done somewhat successfully in many crops (Bauer et al., 1984; Frank et al., 1985). Higher mean daily temperatures generally result in a faster rate of plant development (Yoldas and Esiyok, 2005). Therefore, higher accumulated GDD units per day, decreases the days required to reach specific developmental growth stages in rice. Many of the mid-southern U.S. rice producing states use accumulated GDD from seedling emergence to estimate time sensitive cultural practices, such as mid-season N applications, through their online available DD50 programs. Gauging rice development in this way reduces the physical labor associated with field staging of rice (Downey et al., 1976). Considering the success of this practice to stage rice, we also grouped our NDVI readings according to cumulative GDD to evaluate its potential for scheduling sensor data collection in rice. Five GDD groups were created with a 200 heat unit intervals (Table 3). The resulting five GDD groupings overlapped in the number of DFS to sensing highlighting the different environmental growing conditions observed across the many variety site-years. This was further evident by the variation in observed physiological growth stages within each GDD grouping. Seventeen variety site-years were sensed at the PD stage of development in the current study. The GDD groups 1301–1500, 1501–1700, and 1701–1900 covered two, seven, and six variety site-years where rice was at PD, respectively, with 2 PD sensings occurring when the rice had <1300 accumulated GDD units. All regression analysis between NDVI and grain yield was significant ($P < 0.001$) for all GDD groups. The 1301–1500 and the > 2100 GDD groupings were the weakest predictors of yield potential as determined by r^2. The weak prediction from the 1301–1500 grouping was most likely due to the yield potential still developing after the NDVI measurement,

Table 3. Coefficients of determination of the yield potential predictive models using normalized difference vegetation index (NDVI), NDVI/number of days from seeding (DFS) to sensing, and NDVI/cumulative growing degree days (GDD) as predictors for different growth stage and GDD groupings.

Sensing timing	No. of DFS	Cumulative GGD	No. of site-years (site-years at PD)†	NDVI	NDVI/DFS	NDVI/GDD
					r^2	
Growth stage						
Panicle initiation	41–71	1179–1607	18	0.36‡	0.39	0.36
Panicle differentiation	48–77	1122–1865	17	0.42	0.24	0.19
50% heading	72–94	1868–2717	17	0.26	0.21	0.13
GDD group						
1301–1500	53–71		8(2)	0.28	0.20	0.28
1501–1700	59–81		14(7)	0.41	0.38	0.37
1701–1900	66–84		11(6)	0.41	0.38	0.36
1901–2100	73–90		15(0)	0.49	0.41	0.45
>2100	73–97		13(0)	0.37	0.29	0.30

† PD, panicle differentiation.

‡ r^2 values of the power function models which best described the relationship of different vegetative indices and rice grain yield.

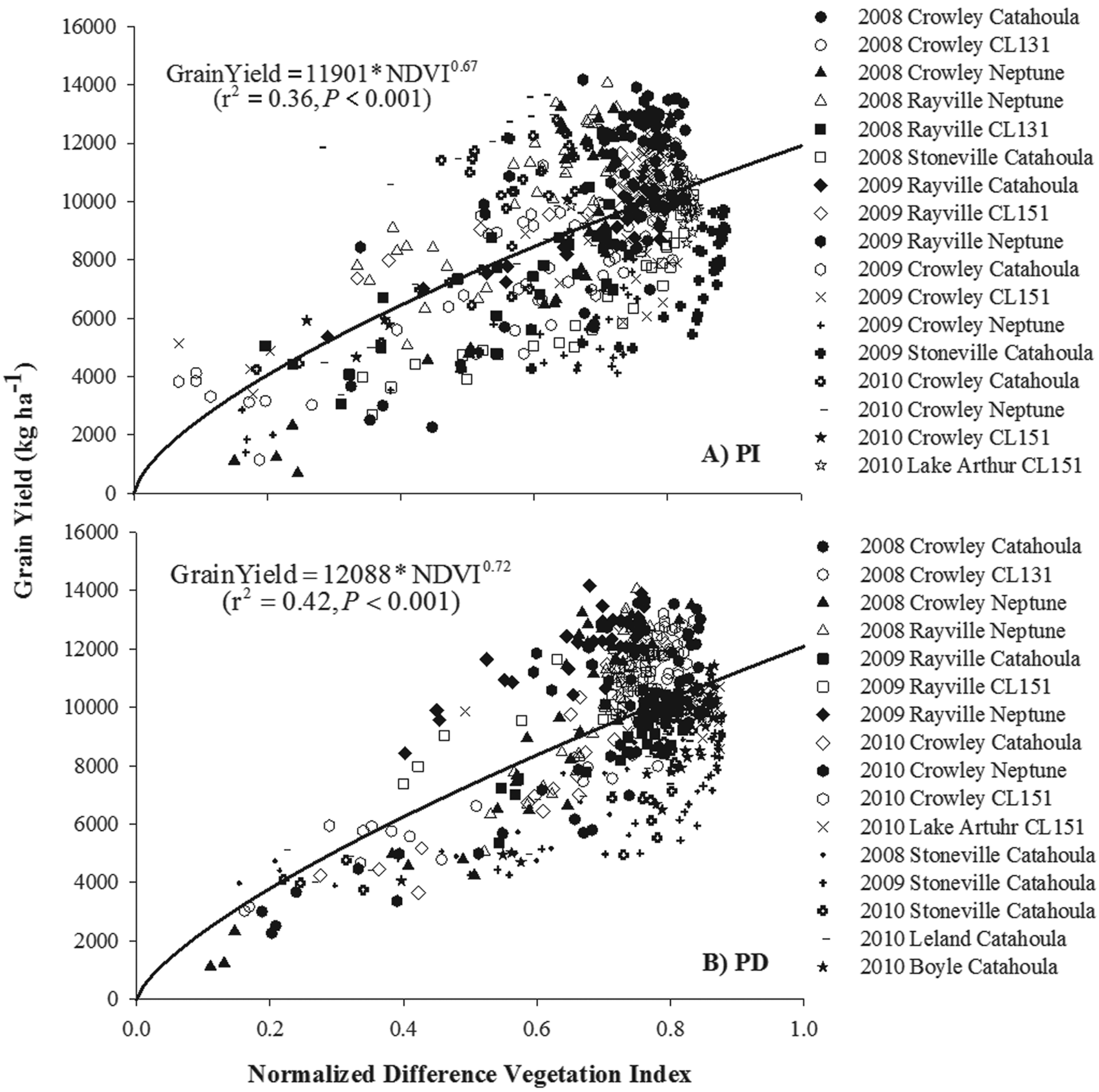

Fig. 2. Relationship of rice grain yield and normalized difference vegetation index (NDVI) collected at panicle initiation (PI) and panicle differentiation (PD) growth stages from multiple variety by N trials at locations in Louisiana and Mississippi from 2008–2010.

while the later grouping could be attributable to sampling times occurring after the onset of panicle emergence. The 1901–2100 GDD grouping was the best predictor of rice grain yield potential; however, it is important to note that all the rice from the variety site-years modeled in this grouping were beyond PD at the time of sensing. The resulting regression from the 1901–2100 GDD grouping is impractical for use in mid-southern U.S. commercial rice production since state guidelines do not recommend mid-season N fertilization beyond PD for nonhybrid rice cultivars (Wilson et al., 2006; Walker, 2008; Harrell et al., 2009). The GDD groupings 1501–1700 and 1701–1900 contained more than 76% of the variety site-years at the PD stage of development in addition to developmental stages before PD, making the yield prediction equations obtained from these groupings more practical for commercial use. Approximately 41% of the variation in grain yield could be explained by NDVI for both the 1501–1700 and 1701–1900 GDD groupings, suggesting that the models are equivalent in their ability to predict rice grain yield. The resulting prediction equations were also very similar for the separate datasets used in the 1501–1700 and 1701–1900 GDD groupings (Fig. 3) suggesting that the ability of spectral reflectance to estimate rice grain yield potential is fairly stable over the 1501–1900 GDD period.

Variation in field conditions and climates across the multiple site-years was observed in both the growth stage and GDD groupings of the NDVI. This was highlighted by the overlap in DFS and GDD in the growth stage grouping and DFS and stage of development in the GDD grouping (Table 3). Normalizing NDVI data for GDD or DFS could account for these environmental sources of variation and has the potential to strengthen yield potential prediction equations. Normalizing NDVI for DFS (NDVI/DFS) would be an estimate of the mean daily biomass production. Normalizing NDVI for GDD (NDVI/GDD) would be an estimate of biomass production in relation to accumulated mean daily temperatures above 10°C. Only the NDVI/DFS normalization at PI improved the coefficient of determination of the regression relationship with grain yield, as compared with non-normalized NDVI, when the sensing time was grouped by growth stage or by GDD (Table 3). All other relationships were reduced. The NDVI/GDD normalization did not improve the regression relationship with grain yield as compared to the unaltered NDVI data. Since NDVI was an equivalent or better predictor of grain yield potential in 15 out of 16 NDVI/DFS and NDVI/GDD comparisons, normalization of NDVI data in rice may not be justified. In a similar study with corn, normalizing

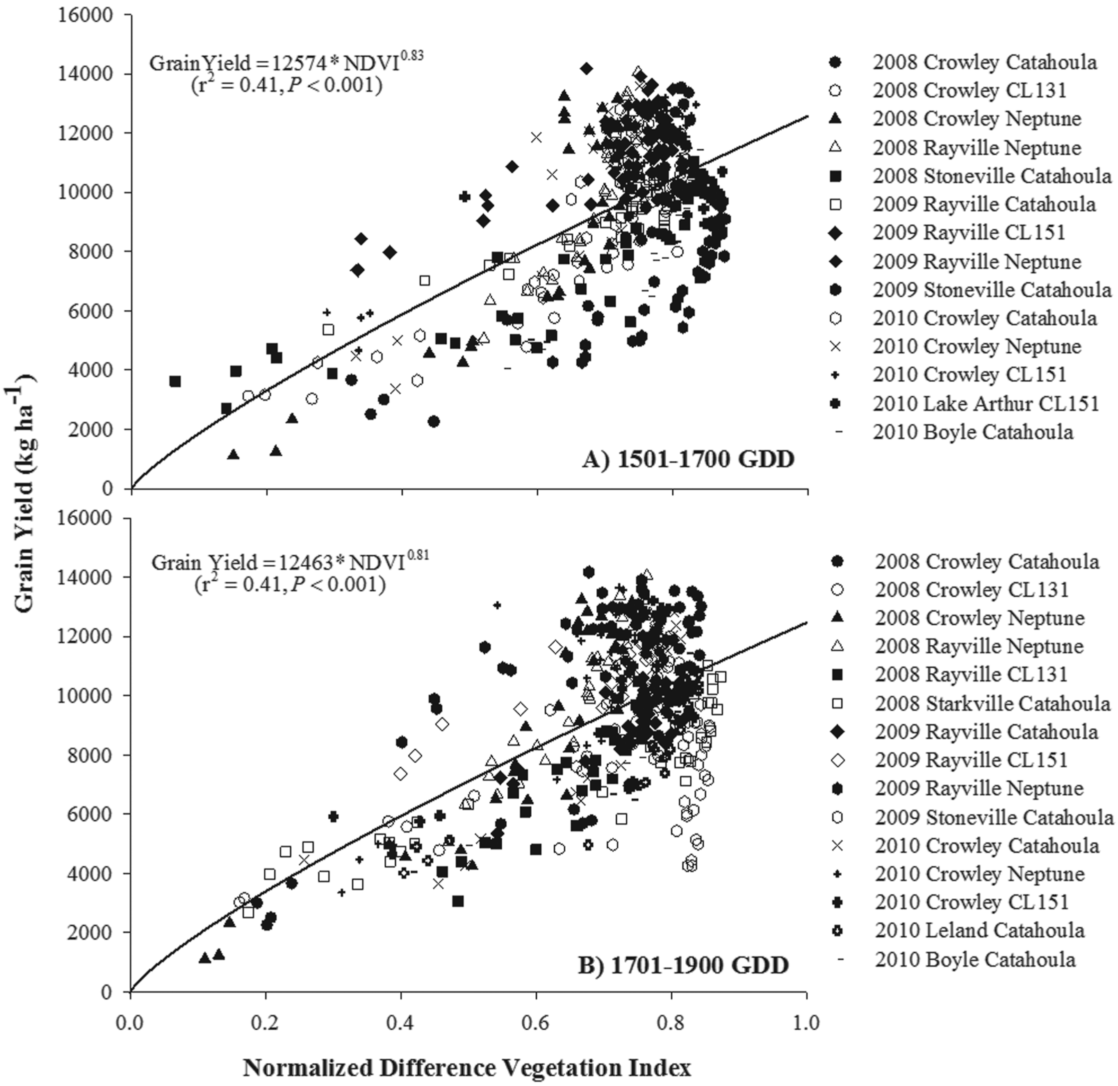

Fig. 3. Relationship of rice grain yield and normalized difference vegetation index (NDVI) collected when 1501–1700 and 1701–1900 growing degree day (GDD) units were accumulated from multiple variety by N trials at locations in Louisiana and Mississippi from 2008–2010.

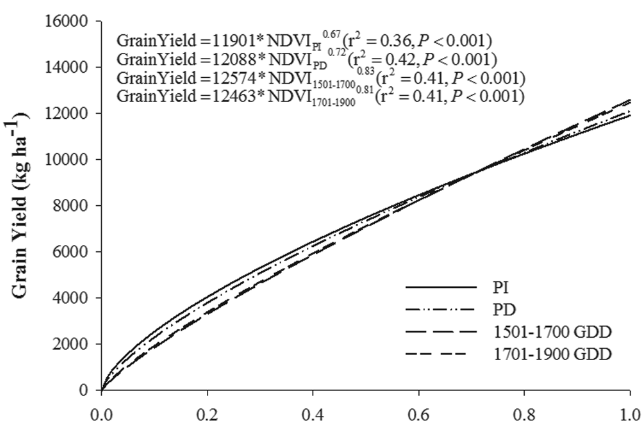

Fig. 4. Combined plot of the power regression functions for the relationship of grain yield with normalized difference vegetation index (NDVI) when the sensor timing is grouped by panicle initiation (PI), panicle differentiation (PD), 1501–1700 growing degree days (GDD), and 1701–1900 GDD from multiple variety by N trials at locations in Louisiana and Mississippi from 2008–2010.

NDVI readings with GDD was also found not to significantly improve the yield prediction over NDVI alone, when the data was grouped by vegetative stage or GDD; however, it was considered to be the preferred predictor of grain yield because it did allow for the adaption of the equation across various climates (Teal et al., 2006). Unlike previous studies with wheat or corn (Raun et al., 2001; Teal et al., 2006), normalizing the NDVI data by either DFS or GDD in our study resulted in a reduction in the equations ability to estimate yield potential in most instances.

Prediction of rice grain yield potential using NDVI is a critical component and a first step in establishing an algorithm that can be used, in conjunction with an in-season estimate of N response to fertilization or response index (Johnson et al., 2000), to determine mid-season rice N fertilization needs. A single yield potential prediction equation for use in commercial mid-southern U.S. rice production may not be the best course of action in establishing the algorithm. Instead, four separate prediction equations are suggested based on the current study. The first two prediction equations estimate rice yield potential at PI or PD (Fig. 2) and would be used when physical field sampling techniques are being used to stage rice. The second two yield prediction equations would be used when GDD units are being used to evaluate rice physiological development in programs such as the state run DD50 programs. One yield prediction equation would be used for sensing between 1501 and1700 GDD and another when sensing between 1701and1900 GDD (Fig. 3). Of particular note, is that the four predictive equations are very similar to each other (Fig. 4) when the equations are plotted together even though separate data sets were used to derive the relationships. In fact, when substituting NDVI values between 0.6 and 0.8 across the four yield potential equations the largest difference in predicted yield is 223 kg ha^{-1}.

CONCLUSIONS

Timing of sensing was a critical component in the establishment of yield potential equations that could be used in mid-southern U.S. commercial rice production. Grouping sensor acquisition timings according to rice stage of development generated separate, yet similar power function regression equations that could explain 36 and 42% of the variation in grain yield at PI and PD, respectively. Sensing post PD reduced yield potential predictability and was not practical according to current mid-season fertilization practices. Grouping sensing timings by GDD generated two equally fitting ($r^2 = 0.41$) power function regression equations between 1501 and 1700 and 1701–1900 GDD. Use of GDD prediction equations would be a logical fit for use in rice DD50 programs where timing sensitive applications, like mid-season N, are estimated using accumulated heat units. Normalization of NDVI data using DFS (NDVI/DFS) and GDD (NDVI/GDD) reduced or did not improve yield potential prediction in almost all instances. The establishment of four yield prediction models for use in mid-southern U.S. commercial rice production provides producers sensible model choices depending on the methodology and sensing window used to stage rice and make mid-season N application decisions.

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